OBLAKI TOČK ZA UPORABO V INFORMACIJSKIH MODELIH GRADENJ (BIM)

POINT CLOUDS FOR USE IN BUILDING INFORMATION MODELS (BIM)

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IZVLEČEK

Oblaki točk se vse pogosteje uporabljajo za pridobivanje podatkov za informacijsko modeliranje gradenj. Upravljalci starejših objektov si prizadevajo za centralizacijo informacij. Dokumentacija o strojnih inštalacijah, cevovodih, električni opremi in preteklih posegih je pogosto shranjena na dislociranih medijih, večinoma še vedno na papirju. Oblak točk je v procesu pretvorbe snovnega v digitalni svet izhodišče, v katerem so podatki o snovnem svetu zajeti na različne načine, kot so fotogrametrija, terestrično ali aerolasersko skeniranje. Ročno modeliranje BIM za upravljanje, vzdrževanje in nadaljnjo uporabo je zamudno, napake so pogoste, zato želimo v izogib napakam proces avtomatizirati. Pojavlja se vse več samostojnih programov in dodatkov za obstoječe programe, ki omogočajo avtomatizirano, hitro in natančno modeliranje iz oblakov točk. V članku predstavljamo rezultate raziskave o možnostih za avtomatizacijo izdelave BIM-modelov iz oblakov točk. Rezultat je polavtomatski postopek modeliranja BIM-elementov iz oblakov točk, ki smo ga preizkusili na konkretnih primerih modeliranja posameznih elementov (sten, cevi in stebrov). Ugotavljamo, da je kljub avtomatizaciji za ustvarjanje kakovostnih modelov še vedno potrebna visoka stopnja uporabniške interakcije.

ABSTRACT

The use of point clouds in extracting data for building information modelling (BIM) has become common recently. Managers of older buildings are working to centralise information. Documentation about mechanical installations, plumbing, electricity, and previous interventions is often stored on scattered media, frequently still on paper. In the transformation of the material world into the digital world, the point cloud is the starting point, containing information about the material world obtained by various means such as photogrammetry, terrestrial or aerial laser scanning. Manual BIM modelling for management, maintenance and future use is a time-consuming and error-prone process. We would like to automate this process and avoid these errors. Recently, there have been developed an increasing number of stand-alone programmes and add-ons that provide automated, fast, and more accurate modelling based on point cloud data. In this paper we present an investigation into the possibilities for automating the creation of BIM models from point cloud data. The result is a semi-automated process for modelling individual BIM elements, which we have tested on specific examples of modelling individual elements (walls, pipes, and columns). We note that despite the automation of the process, a high level of user interaction is still required to produce good quality models.

KLJUČNE BESEDE

terestrično lasersko skeniranje, BIM, oblak točk, samodejna identifikacija objektov, delovni postopek od-skeniranja-do-BIM

KEY WORDS

Terrestrial laser scanning, BIM, point cloud, automatic object identification, scan-to-BIM workflow

1 INTRODUCTION

Current advances in remote sensing are enabling increasingly accurate and content-rich spatial data to be captured in the form of point clouds resulting in the digital equivalent of the material world. Captured point clouds rarely represent the final product, so several commercial programs have appeared on the market in recent years that allow computer-aided design (CAD) and building information modelling (BIM) based on these data.

The use of point clouds in data collection for BIM is becoming increasingly popular. The process of converting captured laser scan data into BIM models is commonly referred to as scan-to-BIM. The industry standard is to manually feed laser scan data into BIM software (Wang, Guo and Kim, 2019). Scan-to-BIM is therefore a manual process carried out by skilled modellers who read the point cloud and manually construct all of the scene's key components (Bassier, Mattheuwsen and Vergauwen, 2019). For large-scale projects with numerous construction elements and complex geometries, such an approach is time-consuming and error-prone, that is why research has been focusing on semi-automatic and automated scan-to-BIM approaches (Wang et al., 2019).

Recently, more and more stand-alone programs and add-ons for existing programs are emerging that allow automated, fast, and more accurate modelling based on raw point cloud data. The working principle of these programs and add-ons is mostly based on shape detection algorithms that simplify the work and reduce the role of the user in the whole process.

1.1 Motivation

Point clouds represent unstructured and semantically empty groups of points that often exhibit noise and similar imperfections that arise during the data collection. While people can visualize point clouds rather well, problems arise when converting this simple point data into information-rich models.

To identify and process shapes that can be encountered in a built environment, robust algorithms are needed. These algorithms must be able to combine simple points into meaningful objects and semantically enrich them so that they have an assigned role in the digital environment.

Software vendors promise simplifications in data processing and exchange, as well as different levels of automation in modelling based on captured point clouds. To test these claims, we examined point cloud datasets and state-of-the-art software capable of modelling point clouds. With them, we created models in which individual building blocks represent structural elements (walls, columns, beams).

The paper begins by presenting methods for point cloud acquisition. This is followed by a discussion of point cloud recording formats, point cloud processing workflows, and an overview of point cloud modelling software. Finally, the workflow for modelling BIM from point clouds is presented and the results are summarised.

2 METHODS FOR CAPTURING POINT CLOUDS

The point cloud is a common expression for a large group of 3D points which includes at least coordinates of points (usually in a Cartesian orthogonal coordinate system). Additional attributes such as scanning reflection intensity or RGB colour value of points may also be included. Point clouds can be obtained through laser scanning or photogrammetry. The latter is gaining more and more popularity due to a huge increase in the availability of drones (Unmanned Aerial Vehicles) and increasingly advanced image processing methods.

2.1 Laser scanning

Classical surveying instruments also known as total stations can perform contactless range measurements and record directions. The essential difference between classical surveying instruments and laser scanners is the speed. Total stations are meant for measuring individual points with aiming while laser scanners measure points in the defined field of view with a defined density without aiming.

Three main principles are used for range measurements in laser scanners. Impulse or "time-of-flight" scanners determine the range through the measurement of time between sending and receiving the light impulses (Hunter et. al., 2003; Abellán et. al., 2006). Phase-shift scanners are more accurate since they observe the shift between emitted and received light waves, but they are slower and can't handle very long ranges (Heritage and Large, 2009). The third type are a triangulation scanners which use the CCD camera on the fixed base with a laser emitter (Franca et al., 2005).

Laser scanners can be attached to different platforms. When scanning from the ground, attached to a tripod, we talk about terrestrial laser scanners. For airborne laser scanning from aeroplanes or helicopters we use the term aero laser scanning and for scanners attached to ground vehicles like cars and trains we use the term mobile aerial laser scanning.

2.2 Photogrammetry

Due to a huge increase in the availability of drones (UAV) and increasingly advanced image processing methods in recent years another manner of point cloud collection appeared. Human can perceive depth with two eyes. The same principle is used in photogrammetry. Two images of the same object collected from two different locations in space, contain the depth information about the object. Finding identical object points in the images, knowing the camera calibration parameters and using central projection equations allows for 3D object points estimation (Grigillo et al., 2015; Mongus et al., 2013; Triglav Čekada, 2017).

The images as raw data for photogrammetric point cloud production can be collected with a camera from hand or attached to a mobile device. Nowadays far most popular is capturing from UAV. For good results, we have to provide images from as diverse positions and directions as possible (Fras et al., 2020).

3 POINT CLOUD RECORDING FORMATS

Many different format types for point cloud recording are available on the market due to different ways of capturing data and hardware. The problem arises with processing programs that can usually import and export only a few format types. The supply on the market is large and increasingly interconnected. Standardization that promote data interoperability has taken of in recent years (Pirotti, 2019).

The data is written in either ASCII or binary formats, some types allow both. The ASCII record is based on a binary basis and writes characters with seven bits. The most common formats with ASCII format are .xyz, .obj, .pts and .asc.

In a binary system, numbers are written with a mantissa and an exponent. Such files are much more compact (4-6 bytes per number) and contain more information. The most common formats with binary are .fls, .pcd, .las.

The third type formats are written as a combination of both methods. The most common formats for combo format are .ply, .fbx, and .e57.

Table 1: List of point cloud record formats (summarized from cloudcompare.org)

Format	**Suffix**	**Binary / ASCII**	**Nr. of point clouds in a single file**
BIN	.bin	Binary	>1
SBF	.sbf	Binary	1
ASCII	.asc, .txt, .xyz, .neu, .pts	ASCII	1
LAS	.las	Binary	1
E57	.e57	Mixed format	>1
PTX	.ptx	ASCII	>1
FARO	.fls,*.fws	Binary	>1
DP	.dp	Binary	>1
PCD	.pcd	Binary	>1
PLY	.ply	ASCII or binary	1
OBJ	.obj	ASCII	1
VTK	.vtk	ASCII	1
STL	.stl	ASCII	1
OFF	.off	ASCII	1
FBX	.fbx	ASCII or binary	1
OUT(Bundler)	.out	ASCII	1
PV	.pv	Binary	1
PN	.pn	Binary	1
SOI	.soi	ASCII	>1
POV	.pov	ASCII or binary	>1
ICM	.icm	ASCII or binary	1
Geo-Mascaret	.georef	ASCII	1

Currently, the most widely used data exchange formats are LAS and E57. For aerial laser scanning LAS format is most commonly used. It can be compressed and saved as LAZ. LAS is an open, binary format specified by the American Society for Photogrammetry and Remote Sensing (ASPRS). It can also be used for terrestrial laser scanner data by ignoring unused fields.

The E57 file format is a compact, vendor-neutral format for storing point clouds, images, and metadata produced by any 3D imaging system. The E57 format was developed by the Data Interoperability sub-committee of the ASTM E57 Committee on 3D Imaging Systems. E57 is a more general format suitable for storing data from various sources. However, in areas where the E57 and LAS formats overlap, they have different solutions to the same problems.

4 POINT CLOUD PROCESSING

4.1 Visualization and organization

Visualisation of a point cloud is generally the first step in end-user needs after capturing the data. Visualization enables visual inspection of captured data, verification of object coverage, possible shadows, holes and adequacy of scanning density.

Two main principles have been established for point clouds visualization: raster images and point-based rendering. The first is more suitable for displaying generally flat objects, such as the surface of the earth seen from an aircraft at aerial laser scanning. Point-based rendering provides 3D data viewing on a flat 2D screen, where the perception of the third spatial component is provided by interactive rotation and scaling of 3D data.

The raw data of a 3D point cloud is generally written as a long list of coordinates along with some additional attributes. To perform further processing it is useful to equip the data with appropriate data structure. It allows to access the data faster and more efficiently in vicinity of the area being processed.

4.2 Segmentation and classification

Point clouds are often used solely for visualization or simple measurements of lengths, angles, and areas. For more advanced applications, segmentation and classification methods might be required. For example: using point clouds, we can capture and segment long road sections (Clode et al., 2004; Boyko and Funkhouser, 2011), forensically review accidents (Laefer and Pradhan, 2006), and capture cultural heritage buildings (Pu and Vosselman, 2009). The measured objects are often large and complex, so it is necessary to segment the obtained data in a meaningful way.

There are some basic strategies to tackle these tasks. Their combinations, adaptations and new methods are emerging constantly. Basic strategies are edge detection (Rabani et al., 2006; Castillo et al., 2013; Grilli et al., 2017), region growing (Besl and Jain, 1988), Hough transformation (Hough, 1962; Kiryati et al., 1991, Xu et al., 1990, Fernandes et al., 2008), RANSAC (Fischler and Bolles, 1981). Advanced strategies using artificial intelligence principles are unsupervised clustering (Morsdorf et al., 2004; Sampath et.al., 2006; Zhu and Shahzad, 2014), super-voxelization and pre-segmentation (Papon et al., 2013) and deep learning-based segmentation (Zhu et al., 2017), which can be further divided into multiview based segmentation (Boulch in sod., 2018), voxel-based segmentation (Riegler et al., 2017; Wang et al., 2017) and point-based segmentation (Qi et al., 2017).

5 POINT CLOUD PROCESSING SOFTWARE OVERVIEW

The initial stages of point cloud processing are usually done automatically using special algorithms, while the final processing is always done manually. Captured point clouds can be imported directly into the BIM modelling software bypassing this pre-processing, resulting in a manual redrawing of the geometry and the addition of information that can be derived from the point cloud or other sources.

The basic functionality of a program for processing point cloud data is a powerful algorithm that allows fast operations using all the hardware capabilities of the computer. When such an algorithm (along with basic segmentation tools) is integrated into software for modelling BIM, point clouds can be used as a reference for manual modelling of components of the BIM model.

Table 2: An overview of the essential features of point cloud modelling and workflow software.

Software	Strengths	Weaknesses	Exchange formats	
			Import	Export
ReCap	- Simple user interface - Processing of large point clouds	- Few exchange formats - Basic processing functions (cropping)	.e57 .pts .rcs	.e57 .pts .rcs
CloudCompare	- Algorithms for working with point clouds (calculating normals, segmentation) - Freely available		.e57 .las .pts .flw .ptg .zfs .dp	.e57 .las .pts .obj .ply .stl .pcd
Revit	- BIM modelling	- Few exchange formats - Not adapted to stand-alone modelling on point clouds	.e57 .pts	
As-Built	- Simple user interface - Qualitative analysis - Collision detection	- Programming interface for Revit only	.e57 .pts .flw .fls .fws	.e57 .pts .flw .fls .fws
Cloudworx	- Modelling of sloping walls- Programming interface for many programs (Bentley, Navisworks, Solidworks) - View 360° photos - Qualitative analysis and clash detection	- Cluttered user interface	.e57 .pts .las .prj .ptg .ptx .dp .zfc	.e57 .pts
EdgeWise	- Maximum level of automation (building skeleton) - Simple user interface - Collision detection - Qualitative analysis	- Programming interface for Revit only	.e57 .pts .dp .fls .rcp .ptg .zfs	.e57 .pts
PointCab	- Modelling irregularly shaped mass elements - Qualitative analysis - Archicad programming interface	- Minimum automation - Does not allow collision detection	.e57 .pts .las	.e57 .pts

In the following, we present some of the well-established software solutions that allow working with the point clouds. The features of established software solutions that allow working with point clouds and the exchange formats they support are summarized in Table 2.

6 PROPOSED SCAN-TO-BIM WORKFLOW

Automated modelling from point clouds has appeared in the literature in recent years (Antova et al., 2016; Antova and Tanev, 2020; Bassier et al., 2019; Pătrăucean et al., 2015; Rodríguez-Moreno et al., 2018; Son, Kim and Turkan, 2015; Wang et al., 2019). The whole process of transforming the material world into BIM models is done in several steps:

- In the first step, spatial data is acquired using a laser scanner or photogrammetric methods. At this point, the captured and raw point cloud can be the final product or, as in our case, it can serve as the basis for further work.
- The second step is to process the point cloud for further work. In this study, we used CloudCompare and Recap software to segment, classify, crop, and remove noise from the point cloud.
- The processed point cloud forms the basis for the third step, in which we prepare the cut-outs before modelling the walls in the chosen modeller. For this purpose, we used Revit. This step is optional and can be omitted when modelling columns, pipes and beams.
- In the fourth step, we select the reference points, which are mandatory for the algorithms used to determine and spatially position the elements. For this purpose, we used the software As-Built within the Revit environment.
- In the last step, we control the element, perform a graphical control of the deviation of the element from the point cloud and detect possible collisions. If the results are poor, we can return to step 4 and repeat the selection of reference points, or we can go to step 2 of the processing and continue working on the point cloud. The final result is an accurate model based on the point clouds.

For the modelling, we used Autodesk Revit software and Faro's automated modelling add-on As-Built which serves as an extension to the base software. We chose this add-on because it supports automatic modelling by selecting a few reference points. The structured user interface makes it easier to work within a single assembly. Figure 1 below shows the entire modelling workflow.

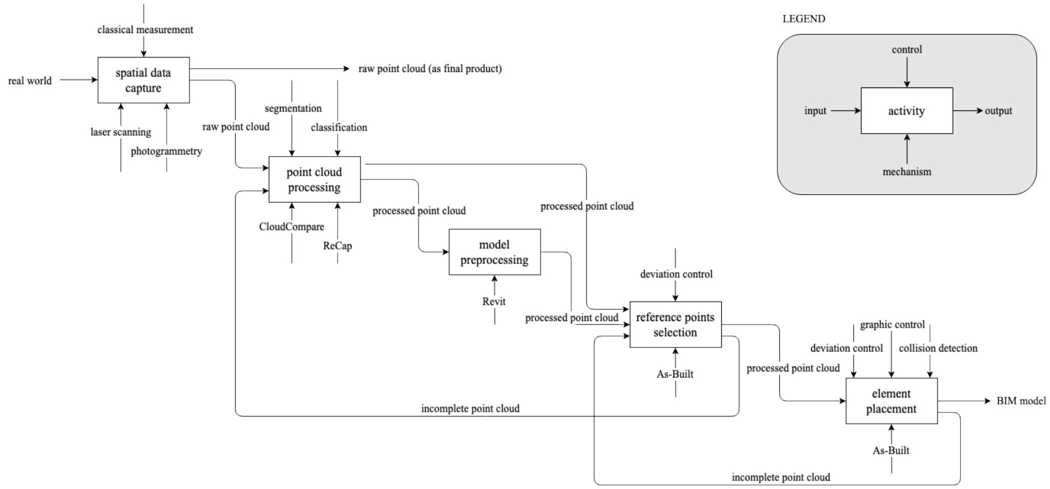

Figure 1: IDEF0 diagram of conversion from the material world to BIM model.

Since most of the main steps in converting point clouds into a BIM model are specific to each task and resulting BIM elements, the workflows are presented through the individual use cases below. The modelling of walls, beams, columns, and pipes is divided into separate sections explaining the process of selecting reference points and placing elements, as well as the overall analysis within each step.

The process of spatial data acquisition has not been covered in detail as it is beyond the scope of this study. Leica BLK360 imaging scanner was used for this study. Out of three available density settings, we have used the middle one (10 mm at 10 m) that produces ~18 million points per setup.

Before modelling, the point cloud must be adjusted and prepared. More on the theory behind was explained in Section 4. We start with the process of data preparation and point cloud processing, followed by model preparation, which is crucial for high quality and accurate wall models.

6.1 Modelling of walls

Point cloud processing

In the case of wall modelling, the basis is an edge detection algorithm that extracts the edges of each element from the prepared view and displays them as a skeleton. The point cloud is thus mapped from three to two dimensions and the points of the point cloud are mapped to pixels. To improve edge detection, it is useful to specify the elements that should be visible in the modelling process. We want to have as little noise and shadows caused by objects in space as possible.

Model pre-processing

Each floor should be designed to minimise superfluous objects and noise that could interfere with algorithms and user modelling. A portion of the point cloud is cut at the desired height. To avoid points on the floor, the cut-out is done above the floor of each floor. After some experiments with different point clouds, it has been found that the best height for the lower part of the cut-out is 1.5 m and for the upper part 2 m. This avoids the various objects including chairs, tables, sinks and radiators. Some objects, such as cupboards, that are as high as the room are difficult to avoid in this part of the process. On the other hand, windows and parapet walls will be captured at this cut-out height. It is important to be aware when working that the perfect case may not be achieved.

Figure 2 shows two cut-outs at different heights, both 30 cm thick. On the left, the lower cut-out is at 1.8 m, where the skeleton of the rooms and some cupboards can be seen. This cut-out makes the room view more transparent. The right cut-out has a height of 1.2 m and contains much more distracting objects. In addition to the height, the thickness of the cut-out is also important. The larger the thickness, the more points from the cloud are shown, which in the case of a less accurate laser image can result in more noise that interferes with detection and reduces modelling accuracy. On the other hand, too few points do not show the whole situation.

There is no ideal recipe for determining the thickness of the cut and its heights; in any case, it is necessary to know the full image of the scanned area and to adjust the parameters accordingly. Each cloud can be further cropped and cleaned of noise in the manipulation software, thus improving the usability even further.

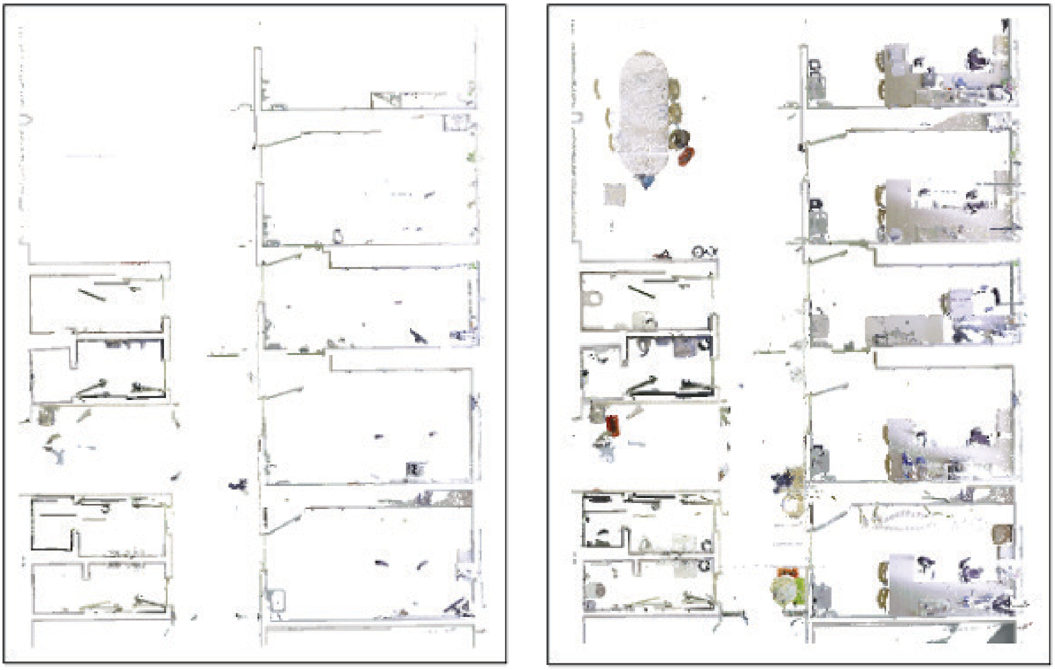

Figure 2: Comparison of an edited (left) and unedited (right) point cloud.

From the prepared view, a modelling base can be prepared. The algorithm converts the selected view from 3D spatial points into a 2D image, which serves as the basis for automated modelling. The image can be embedded in any view or used as a final product, serving as a rough schematic. Combined with well-prepared cut-outs and settings, a good quality basis for automated wall modelling can be produced.

Reference points selection

The upper storey of the modelled wall must be determined, or its height if the top floor limit is not specified. In places where data is missing, the wall can also be defined based on a single recorded side. If only one side of the wall is visible due to obstacles, it can still be modelled. This option proves to be very useful in cases where the laser scans were taken within a single room and there are no connexions to other rooms. In the next step, we choose the start and end points of the wall. The algorithm works based on the user's selection of two or more points to serve as a reference for detection. Since walls are linear elements, two points are sufficient to detect them in well-prepared point clouds. In cases where more noise and surrounding objects are present and the software is not able to detect the course and thickness of the wall with two fixed points, it can be assisted by selecting more points.

Element placement

Interrupted laser beams, noise or shadows do not significantly affect detection, which is important in indoor environments where furniture covers a certain part of the wall and does not need to be moved during the scan. Interruptions due to openings such as doors and windows do not affect the positioning of the wall, as a few points are sufficient for the software to calculate the direction, position and thickness of the wall.

Point clouds may contain objects in the room that obscure the walls at the time of scanning, and which cannot always be satisfactorily removed during processing. In Figure 3, we can see how the cabinet doors cause interruptions in the point cloud. In this case, we defined two points on either side of the wall to locate it in space. The algorithm also connects the wall at the breakpoints, creating a continuous wall in the program. In Figure 3, the path of the wall is shown in orange.

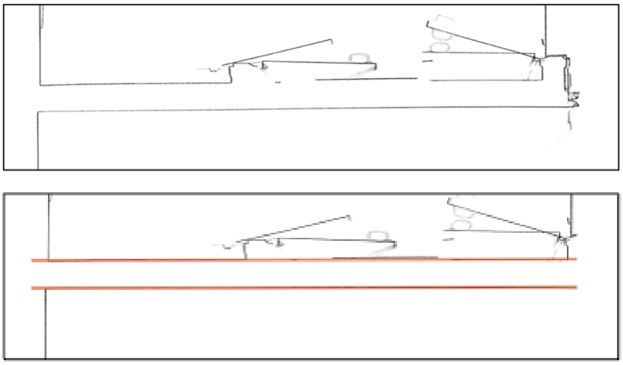

Figure 3: Detection and placement of a wall on a floor surface obstructed by a cabinet.

Another example is interruptions due to shadows in laser imaging. Figure 4 shows a situation where, at the time of scanning, a door obscured half of the wall and caused a shadow in the point cloud. Based on this situation, we know that the wall continues even at the point where the points were not scanned. The algorithm assembles the wall into a complete whole and determines its thickness based on the known portion that is fully visible on the left. The course of the wall is shown in orange in Figure 4.

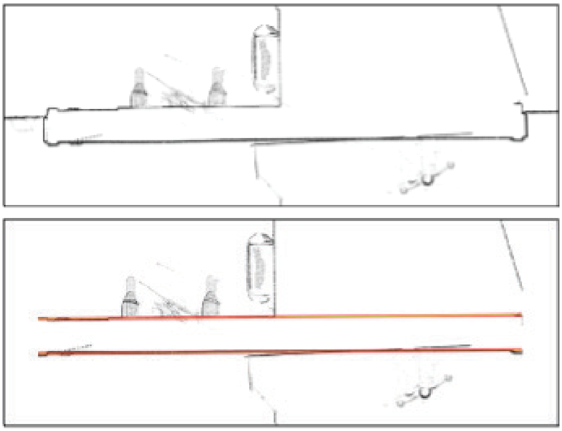

Figure 4: Detection and placement of a wall on a floor surface with interruptions due to shadows.

If the wall is covered by objects along its entire length and their configuration does not require them to be moved during the scan, we can use a detection algorithm based on a single visible surface. In this case, a short, uncovered section of the wall on the left side was used to determine the direction and thickness. The solid orange line in Figure 5 shows the side from which the wall is determined, while the dashed line represents an approximation based on the visible portion on the left side.

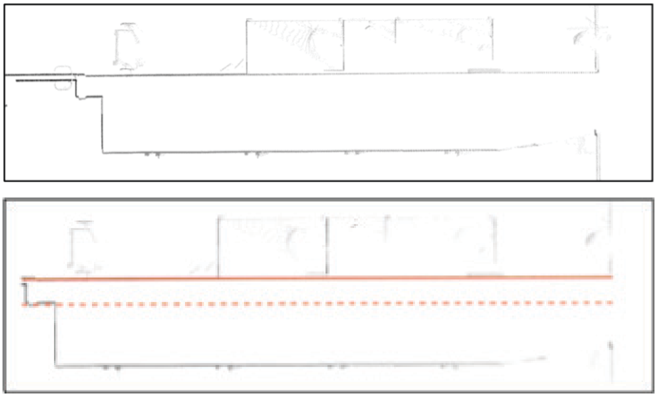

Figure 5: Detection and placement of a wall based on a single visible wall surface.

Deviation analysis

Based on the deviation analysis, the user can identify different categories of modelling errors, which are divided into three groups for better understanding: positional, geometric and orientation errors:

- Positional errors can occur when there are constant values of misalignment along the entire wall. For example, if there are positive deviations on one side of the wall and negative deviations on the other side, the wall model is misaligned. In this case, it the wall would need to be replaced or repositioned.
- If the thickness of the wall model is incorrect, it is a geometric error. This error can be detected if the deviation values on both sides are positive, which means that the wall model is undersized. Negative values on both sides mean that the wall model is too thick. The solution to such a geometric error would be to correct the thickness.
- An orientation error can be detected when the misalignment values increase or decrease from one side of the wall to the other. In this case, the wall model is rotated and need to be aligned.

Figure 6 shows the analysis of point deviations concerning the modelled wall.

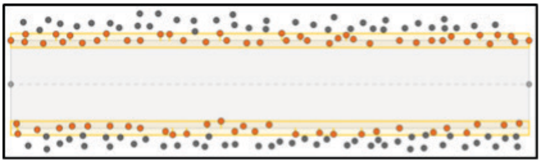

Figure 6: Graphical representation of the analysis of point deviations concerning the modelled wall.

In all this, the location quality of the point cloud also plays an important role. Despite sufficient point density, the quality and correct placement of the point cloud in space must be guaranteed. It must not be rotated in any direction or otherwise distorted.

6.2 Modelling of pipes

Point cloud processing

Modelling pipes in space does not require the same preparation as modelling pf walls; it is sufficient to isolate the pipes in question from other objects. Due to vertical and horizontal paths and overlapping, it is difficult to represent pipes in 2D, so they are treated as a spatial problem in 3D.

Reference points selection

After selecting the start and end points of the pipe, the selected points are used to determine the path of the pipe on a reference point cloud, as shown in Figure 7.

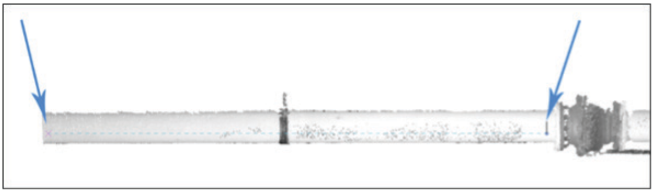

Figure 7: Selection of reference points on the point cloud for pipe placement.

In many cases, the point cloud is not ideal because pipes are located at the corners of walls and are close to walls or overlap due to interference. A laser scanner in practice rarely captures all sides of the pipes due to occlusion. This lack of data must be carefully considered in modelling if good results are to be achieved.

Element placement

If the pipe is below the ceiling and the top of the pipe is not visible due to the location of the data capture, the accessible half can still be used to determine the radius, complete the pipe and position it accurately in space. Figure 8 shows the accuracy of the positioned pipe model within the incomplete reference point cloud. In some places the noise is minimal, but in this case, it is not significant enough to interfere with the automatic algorithms and affect the accuracy of the detection. In several cases, we have successfully created pipe models with incomplete data.

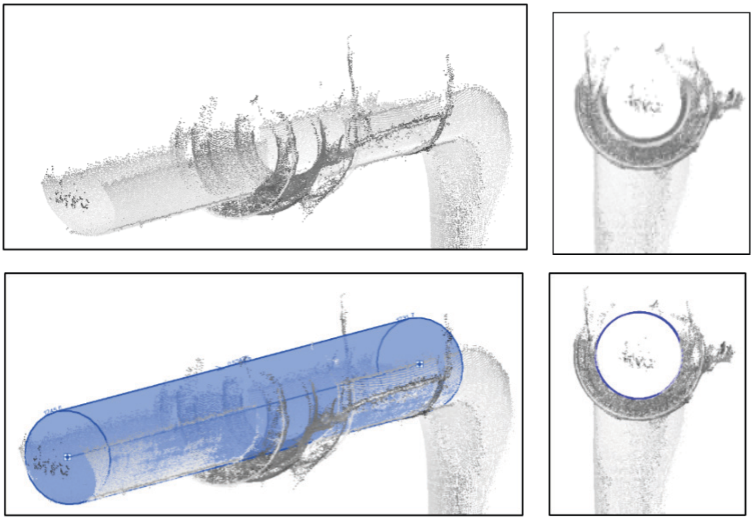

Figure 8: Modelling a pipe with half the known points.

If the pipe is in a corner, the laser scanner can only detect a quarter of its diameter. By selecting two points on the reference point cloud, it is possible to precisely define and position the pipe model in

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space. Similar to the first example, we successfully placed the element in space despite the incomplete data. The Figure 9 shows the pipe model within the point cloud.

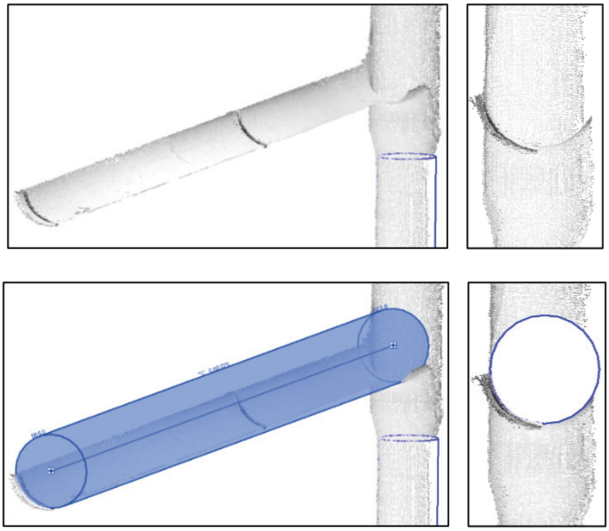

Figure 9: Modelling a pipe with a quarter of the known points.

Unfortunately, there are also cases where algorithms fails. The room had two insulated pipes under the ceiling that broke at the knee several times (Figure 10: left). Due to the heavy noise, it was not possible to automatically determine the diameter and location of the pipes (Figure 10: right). In such cases, the solution is manual modelling, which is not as fast and accurate as semi-automatic modelling.

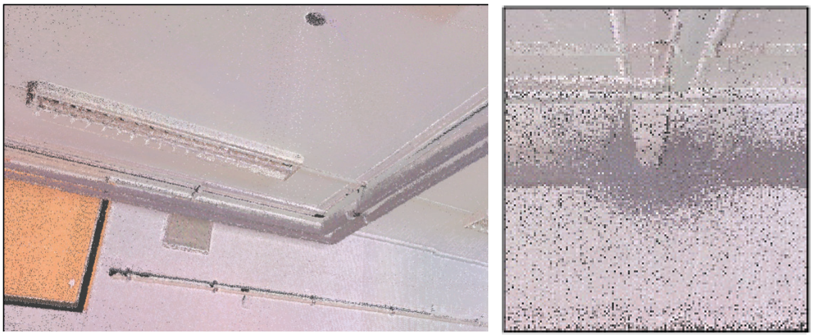

Figure 10: View of two pipes in the room. No noise is visible in the left image. The right image shows a cross-section of the pipe in which noise can be seen.

The pipes in the room must be connected to form a meaningful whole. The software analyses all existing element families and determines the variable parameters that can be used for the connections. When importing additional families that were not included in the original analysis, the additional pipes are analysed again. To connect separate parts, it is necessary to mark the free ends of the pipes to be connected. The selected ends of the pipes are colour coded to visually distinguish them from the rest of the pipes. In Figure 11, the arrows indicate the selected ends of the pipes to be joined.

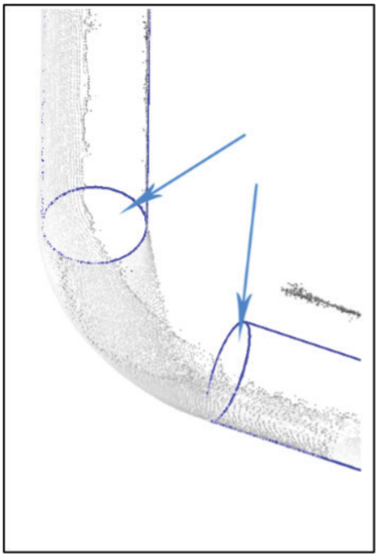

Figure 11: Selection of the free edges to be joined.

Based on the input points lying perpendicular to each other, the software selects a knee piece with a fitting radius that exactly fits the point cloud.

Deviation analysis

The algorithms in the previous subsection aim to find and model connections that are as similar as possible to the point cloud we are starting from. However, after the modelling is complete, in most cases the model still does not satisfy the required consistency conditions. As each component is modelled separately, minor discrepancies and inconsistencies occur because the components are not connected into a complete whole. This is the case when components are positioned at wrong angles, parts protrude or gaps exist between them. The software transparently flags these inconsistencies. The correction algorithm changes the position of the raw axis (it iterates through the elements until the internal conditions are met: the tolerance between joints or the number of iterations at each joint). It moves the axis only minimally and rotates the connections between the pipes, resulting in an accurately connected model. If the algorithm does not find a result within the specifications, the precision of the iteration parameters must be slightly reduced to achieve the connection of the individual elements into a complete whole. This leads to slightly worse, but still acceptable results. Perfect joints between pipes are important for the analysis of the flow through them.

As with the walls in the previous subsection, the accuracy of the model can be determined relative to a reference point cloud for the pipes and their joints. In Figure 12, the light green colour indicates the positions on the element that differ from the point cloud by a few millimetres. Despite imperfect point clouds containing some shadows and noise, we can create BIM models with the maximum accuracy that we can control throughout the process.

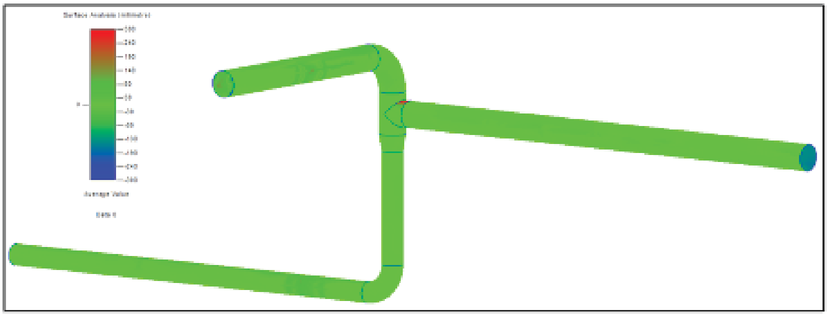

Figure 12: Display of the deviation of the modelled pipes from the original point cloud

6.3 Modelling of beams and columns

Point cloud processing

The workflow for modelling columns or beams is similar to that for modelling pipes. As with pipes, it is not necessary to create a 2D template for columns and beams before starting. It is sufficient to clip the parts of the point clouds to be modelled and temporarily isolate them from the environment so that they do not interfere with the spatial representation of the user and the modelling algorithm.

Reference points selection

First, the type of element to be modelled must be selected. When selecting a column, the lower and upper levels must be selected. When selecting a beam, only the lower plane can be specified. To model the element, two reference points are selected in the point cloud to represent the beginning and end of the element.

Based on the cross-section of the point cloud, the automatic algorithm searches the element library for the element that best matches the cross-section. Once the comparison is complete, a pop-up window is displayed with the best matching element according to the selected points in the point cloud.

Element placement

If the point cloud in some areas is too sparse, we can use the part of the element where the point cloud is more dense. The type and dimensions of the steel section are specified along its axis. If we, for example, know the width of the two webs and their distance from each other, we can determine the dimensions of the flange. The Figure 13 shows an example of a steel I-section with half of the flange missing due to obstacles in the capturing process.

The distance and angle between the acquisition source and the steel profile always result in slightly poorer data quality. The points are much sparser and not all parts are captured due to obstructions.

Of course, we may not know the dimensions of the top flange, but we do know the dimensions of the web and the bottom flange. The program uses the known dimensions to determine the missing ones if they match the known ones. Starting from the two selected points, the program determines the dimensions and the position of the element in space.

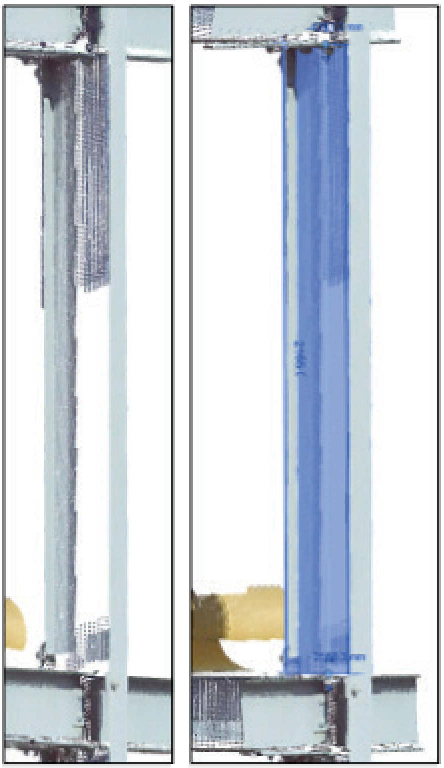

Figure 13: Steel section with missing part of the stand (left) and modelled element based on the point cloud (right).

7 DISCUSSION AND CONCLUSIONS

In nature, buildings and walls are not always perpendicular and parallel to each other, and this must be considered when modelling the actual situation. As explained before, Leica BLK360 imaging scanner with density set to 10 mm at 10 m was used for this study. According to our experience, this density setting results in the best balance between accuracy and size of the point cloud for our task.

At the time of data collection, there are many obstacles in buildings that cause shadows and noise. Modern BIM software tools have the advantage of using algorithms that use reference points to determine the dimensions of elements and place them in the point cloud.

This allowed us to model walls that were largely obscured by the shadows of other objects - based on known data, modern tools predict and complete the path of the walls. The quality of the model was checked during the modelling process and the results were displayed graphically at the end of the run. The dimensions of the features and their spatial location were determined using a reference point cloud with millimetre accuracy. The main limitations of the existing algorithms were irregular and sloping walls and walls with variable thickness that the software could not detect and locate.

The main problem in modelling pipes and their joints is that pipes in rooms are often intertwined and overlapping, so not everything can be detected in situ. The software, therefore, interpolates the diameter of the pipes and places them accurately within the known data. In this way, we can determine the pipe diameters and locate them accurately in space, even if only half or a quarter of the pipe has been captured. With such software support, the process is significantly shortened. Not only is less time spent collecting all the data in the field, but the modelling phase is also shortened. In the examples, it has been shown that the speed of modelling is not at the expense of the accuracy of the model. In addition to the modelling, the software allows the quality of the model to be checked against a reference point cloud and the various deviations to be displayed graphically. The spatial accuracy and dimensions of the models were determined to the nearest millimetre compared to the reference point cloud. The problem manifested itself in the form of noise in the acquired data. In our cases, the noise distorted the shape of the pipe so that the software could not detect and identify the pipe. It should also be noted that this method only covers the outer geometry of the pipes. In most cases, the inner diameter is equally important or even more important.

When modelling columns and beams, the data capture problem is that it is usually impossible to capture seamless data due to overlap and shadowing. For concrete columns, two sides are often captured, while for steel beams, only the webs or flanges are captured. By selecting reference points within the point cloud, the data is analysed and the types of columns and beams are determined. In the first case, the programme was used to determine the dimensions of the columns where the webs were captured but the flange was missing. In the second case, the situation was similar, where a web and one flange were known. Automation makes the workflow faster and the determination of the elements more accurate. However, it is important to be aware that using automated algorithms to fill in missing data can also lead to erroneous results. Therefore, it is important to keep checking intermediate steps and to control the final result.

The strengths of the approach studied lie in the accuracy and increased speed of data processing and modelling. The recurrent and ongoing analysis of the quality of the models created leads to better results. On the other hand, there are some problems that still need to be solved. Most of them are related to software vendors, as interdisciplinary integration of file formats is not yet mature or even missing. Instead, the major software vendors rely on proprietary file formats and lock users into selective software ecosystems. They are also passive and slow to evolve their software to work with point clouds. On the other hand, there are gaps in methods and algorithms for automatic identification of objects. One such example is non-typical structural elements, which currently need to be modelled manually. Typical structural elements also currently require a lot of user interaction.

Nevertheless, we found a certain level of automation that allows users to identify objects faster and more accurately, which is confirmed by similar examples in the literature. The automated approach allows for greater speed and accuracy than manual modelling, as ClearEdge3D has confirmed with similar examples (ClearEDge3D, n.d.). Despite the use of a different programme, final results were 60% faster than traditional manual modelling with similar workflows. The accuracy of the automated BIM point cloud conversion process compared to a manual process has also been demonstrated in similar examples by several researchers over the years comparing the qualitative results of the same features modelled manually and automatically (Macher, Chow and Fai, 2019; Patraucean et al., 2015, Qu and Sun, 2015,).

The current workflow is semi-automated, where the user triggers automatic processing by selecting a set of elements and reference points within the cloud. Full automation, where the software would semantically identify specific building parts from the point cloud without user interaction, is not currently possible. The closest thing to this is ClearEdge3D's EdgeWise software, which allows automatic modelling of the wall skeleton of buildings. However, accuracy is still poor and the result is a schematic building model rather than a detailed BIM model. The leading software vendors (Autodesk, Bentley Systems and Nemetschek Group) are currently slow to develop interfaces for working with point clouds in their software. The most promising path to full automation appears to be through deep-learning algorithms that use large databases to identify individual elements within a point cloud, locate them spatially, integrate them, and perform quality control throughout the process. Despite advances in deep learning algorithms, the theoretical limitations of extracting information from point clouds remain. For example, despite new algorithms, it will not be possible to extract non-geometric information to further improve the model because semantic enrichment (e.g., material of the element, type of element, internal structure, internal geometry) of the modelled geometric features is even more challenging and requires more manual input, additional input data (besides point clouds), and even more advanced methods.

Further research in this area needs to focus on improved automation of the workflow leading to less interaction with the user. This will undoubtedly need to be achieved through better algorithms and artificial intelligence approaches (e.g. Deep Learning). Last but not least, software vendors will need to follow the advances and develop solutions that enable the entire workflow from capture to final model. This would allow the AEC industry to benefit and evolve from point clouds.

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